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Composite Digital Content Optimization

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Composite Digital Content Optimization

BACKGROUND

Many composite digital content items (*e.g.* ad creatives) comprise multiple digital content items (*e.g.*, multiple assets – video content items, audio content items, etc.). In some cases, there may be a very large number of number of possible digital content items combinations that can be used to form a composite digital content item (*e.g.*, in response to a request for digital content from a user). In these cases, it is difficult for the content provider to select which particular digital content items, from the very large number available, to provide. While the content provider could, in principle, send randomly selected composite digital content items to the user to obtain information about their preferences, it is likely that this would entail sending the user many composite digital content items that they do not want to watch - and the processing and network resources used in generating these composite digital content items and transmitting them to the user are wasted.

SUMMARY

This document describes a system for the dynamic tracking performance of individual digital content items (*e.g.* assets) that are included by multiple, composite digital content items (*e.g.*, ad creatives that include multiple different assets). In some cases, an initial weighting of the individual digital content items is determined, and a statistical model is created for each digital content item of the composite digital content items based on such. The statistical model provides adjusting of the weighting of each individual digital content item for each composite digital content item. The statistical model can be re-evaluated using the updated weightings (in an iterative fashion) for each of the digital content items to identify a combination of individual

digital content items for each composite digital content item having a highest scoring/ranking – *e.g.*, highest click-thru-rate, conversion, views, etc. For example, the statistical model can determine that a particular digital content item can perform poorly with a combination of other digital content items for a composite digital content item, but perform well with a different combination of other digital content items for the composite digital content item.

DESCRIPTION OF DRAWINGS

Figure 1 is a diagram of an example system for generation of a statistical model for modeling the performance of digital content items.

Figure 2 is a diagram of an example system for implementation of the statistical model.

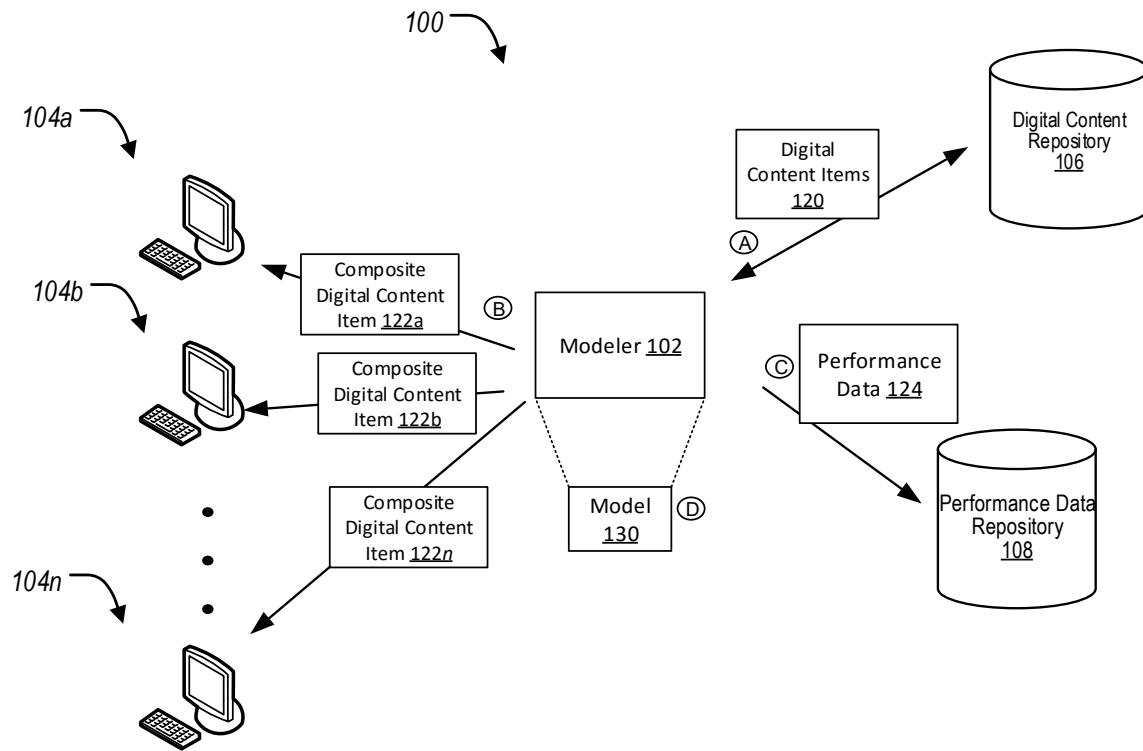
DETAILED DESCRIPTION

Many composite digital content items (*e.g.*, ad creatives) comprise multiple digital content items (*e.g.*, multiple assets -- video content items, audio content items, etc.). For instance, a statistical composite digital content item can include multiple digital content items – *e.g.*, for an ad creative composite digital content item, the assets can include a product image, a company logo, a text title, background color, font size, text, image layouts, etc. In some examples, the composite digital content item can include a video advertisement, which includes such assets as video templates, soundtracks, product images, etc.

Generating composite digital content items (*e.g.*, ad creatives) using all combinations of digital content items (*e.g.*, assets) can be difficult in such cases due to an extremely large number of total combinations of the digital content items (*e.g.*, assets). To that end, to allocate network traffic to the composite digital content items, some possible solutions can include randomized

rotation of the composite digital content items – referred to as exploration – such that each composite digital content item has an equal opportunity to be provided for display (*e.g.*, on an electronic document (webpage)). However, such rotation can waste network bandwidth on low-quality composite digital content items (*e.g.*, ad creatives). In some examples, the composite digital content items can be provided for display based on a historical click-through-rates or historical conversion rates – referred to as exploitation. However, doing such can provide little opportunity to new composite digital content items that have limited historical data. Thus, this document discusses a solution to address this exploitation vs. exploration problem in an effective way to provide an optimal strategy to provide composite digital content items (*e.g.*, ad creatives).

Fig. 1 illustrates an example system 100 for generating a model for modeling the performance of digital content items. The system 100 includes a modeler 102, user device 104a, 104b, ..., 104n (referred to as user devices 104), a digital content item repository 106, and a performance data repository 108. The modeler 102 is in communication with the user devices 104, the digital content item repository 106, and the performance data repository 108 over one or more networks.

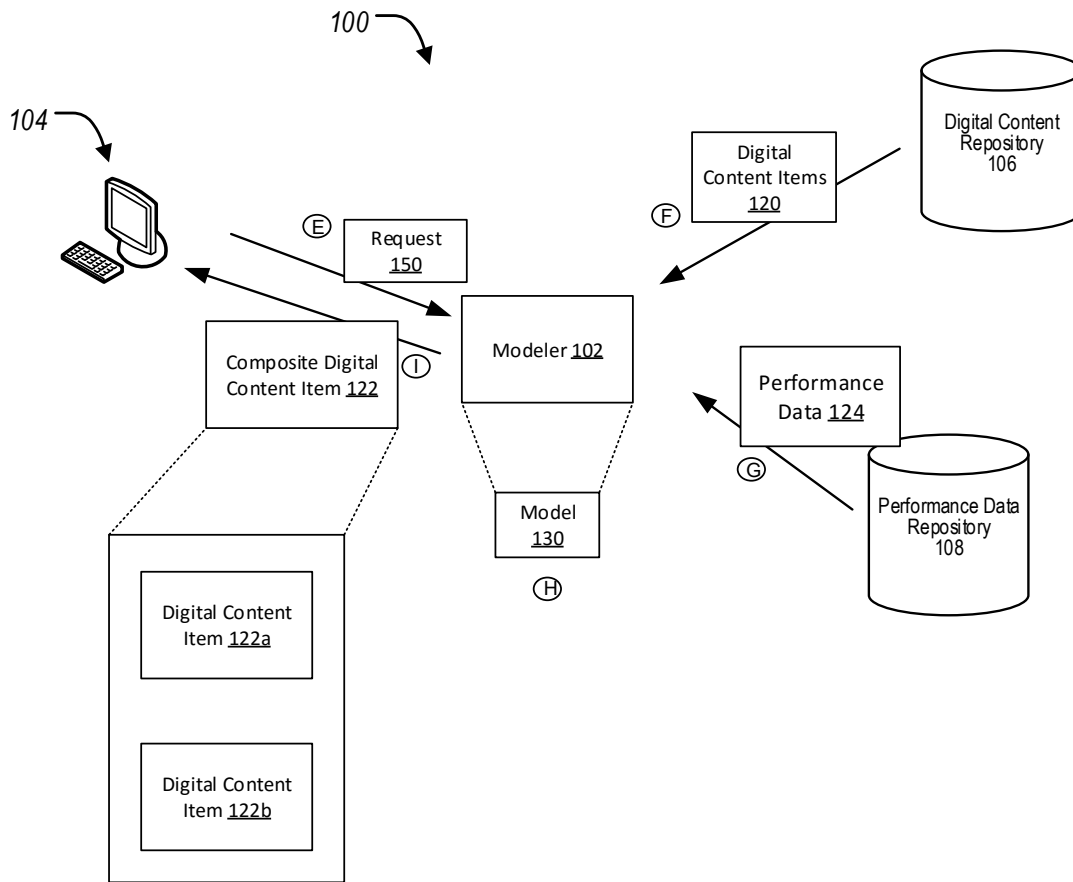


The modeler 102 accesses the digital content repository 106 to obtain digital content items 120, at step A. The modeler 102 creates composite digital content items (*e.g.*, ad creatives) using different combinations of the digital content items 120 (*e.g.*, assets). The composite digital content items are distributed to the user devices 104, at step B. Specifically, the composite digital content item 122a is distributed to the user device 104a, the composite digital content item 122b is distributed to the user device 104b, and the composite digital content item 122n is distributed to the user device 104n. The composite digital content items 122a, 122b, 122n are referred to as composite digital content items 122. In some cases, each of the composite digital content items 122 include at least one different digital content item 120. The modeler 102 collects performance data regarding the composite digital content items 122, including such data as impressions, clicks, conversions, web properties, and other user and publisher data. The modeler 102 stores such performance data 124 in the performance data repository 108, at step C.

The modeler 102 creates a statistical model 130, at step D. The statistical model 130 is created to evaluate the performance of each digital content item 120 (*e.g.* asset) and calculate the Thompson Sampling weight of each digital content item 120 (*e.g.*, asset). In general, the statistical model 130 determines the performance of each digital content item 120 using the (historical) performance data 124. The statistical model 130 includes features such as digital content item identification (ID), digital content item group ID, web property, etc.

The statistical model 130 accounts for uncertainty in determining the Thompson Sampling weights of the digital content items 120 by considering the quantity of the performance data associated with each digital content item 120. For example, for a group of digital content items 120 (*e.g.*, an ad group) where each digital content item 120 has a relatively large amount of performance data 124 associated with each digital content item 120, there is more confidence in predicting the combination of digital content items 120 for the composite digital content item 122 that will provide a desired performance parameter (*e.g.*, click-thru-rate, impressions, etc.). Additionally, for example, for a relatively new composite digital content item 122 – *e.g.*, a composite digital content item 122 with limited (historical) performance data 124 associated therewith (as compared to other composite digital content items 122), the statistical model 130 provides opportunities for such by assigning larger Thompson Sampling weights to digital content items 120 of this new composite digital content item 122.

Fig. 2 illustrates the system 100 implementing the statistical model 130. The modeler 102 receives a request 150 from one of the user devices 104, at step E.



The request 150 can be a request for digital content, such as video content, image content, audio content, for display on an electronic document (e.g., a web page). The modeler 102, in response to the request 150, obtains digital content items 120 from the digital content repository 106, at step F. In some cases, the obtained digital content items 120 are based on the request 150 (e.g., responsive to the request 150). The modeler 102 further accesses performance data 124 from the performance data repository 108, at step G. The statistical model 130, based on the obtained digital content items 120 and the obtained performance data 124, generates a composite digital content item 122, at step H. Specifically, the statistical model 130, selects the digital content items 120 for the composite digital content item 122 based on the Thompson Sampling weights of the digital content items 120. That is, the statistical model 130 selects the digital content items 120 such that the composite digital content item 122 (that includes the selected

digital content items 120) has the estimated greatest probability that the composite digital content item 122 will have the greatest desired performance parameter (*e.g.*, click-thru-rate, impressions, user interaction, etc.). The modeler 102 provides the composite digital content item 122 to the user device 104 (in response to the request 150), at step I. The composite digital content item 122 can include a first digital content item 122a and a second digital content item 122b.

In some cases, the statistical model 130 updates the Thompson Sampling weights for the digital content items 120 continuously – that is, as each time a digital content item 120 is provided within a composite digital content item 122 to the user devices 104, the performance data 124 is obtained and the statistical model 130 updates the Thompson Sampling weights for the digital content items 120 instantaneously (or near real-time). In some examples, such updates can be performed hourly, or daily.

The system 100 provides several advantages, including balancing of the exploitation v. exploration issue – that is, the system will explore more when the performance data 124 is limited for the digital content items 120, and will exploit more when a digital content item 120 has significantly better performance than others. Further, the system 100 can be updated if there is a change in the environmental landscape of the system 100, or a user preference is detected, such that the statistical model 130 will capture this change and adjust the Thompson Sampling weights accordingly. Moreover, the system 100 can be combined with other previous systems, such as pure exploration systems and/or rotation systems.

ABSTRACT

A digital content rotation system that distributes digital content items a sufficient number of times to generate a statistical model for prediction of performance of the digital content items, while also preventing overall system degradation of content provided by content providers. The predicted performance of various digital content items is used as weights in a distribution rotation, thereby providing an optimal balance of exploitation and exploration of content performance.